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RESEARCH ARTICLE

MASS ROBOT: PREDICTIVE MAINTENANCE USING STACKED CNN BI-LSTM FOR CLEANING ROBOTS

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Abstract – The vibration of mobile cleaning robots can indicate performance degradation or operational safety issues. Therefore, it is crucial to identify the cause of vibrations at an early stage in order to prevent functional loss and hazardous working conditions. To overcome these drawbacks, a novel Maintenance using SCB-LSTM (MASS) Robot system has been proposed for enhanced maintenance planning and real-time fault detection in cleaning robots. Initially, vibration data is collected during the robot's operation. This data is processed through a Stacked Convolutional neural network Bi-directional Long Short-Term Memory (SCB-LSTM) model to identify specific sources of vibration. The information is then sent wirelessly to a remote monitoring application, allowing users to track the robot's condition in real-time and diagnose issues efficiently. The suggested MASS technique has been assessed using a MATLAB simulator. The efficacy of the suggested MASS approach has been evaluated by utilizing parameters such as F1-score, recall, accuracy and precision respectively. The proposed MASS method achieves better accuracy of 79.8%, 85.4%, and 88.1% than GPM [20], DBF [23], and KPM [25] methods.

Keywords *– Predictive maintenance, Real-time fault detection, Stacked CNN Bi-LSTM, remote monitoring.*

1. INTRODUCTION

Nowadays, mobile cleaning robots are ubiquitous, being used everywhere from industries, homes, hypermarkets, airports, hospitals, and food courts to vacuum, mop, and sanitize [1]. In order to prevent malfunctions, catastrophic failures, and customer dissatisfactions, the robotic cleaning system needs to be maintained and deployed in an environment that is friendly to robots [2,3]. At present performance degradation and safety-related problems with professional cleaning robots are commonly observed through manual supervision. Unfortunately, the lack of past failure data makes it labor- and skill-intensive, time-consuming, and difficult to implement, particularly with the recently developed sophisticated cleaning robots [4–7].

Furthermore, other problems including prolonged downtime, component underutilization, safety concerns from sudden failure, and high operating and maintenance expenses could be brought on by this periodic manual approach [8]. These difficulties are avoided by automated predictive maintenance techniques [9]. They are frequently employed in industrial robots and automobiles for continuous health tracking, efficiency decay prediction, hazardous operating conditions detection, and security system failure notification [10–12].

Predictive maintenance (PM) based on artificial intelligence (AI) has received a lot of attention especially for automated PM design. For fault identification and classification, it uses Machine Learning (ML) and Deep Learning (DL) models [13–15]. In order to provide a secure and effective service in a complex and dynamically changing environment, detect any efficiency decay, and prevent operational security issues, autonomous mobile cleaning robots are mandated to use the PM system [16–19]. To overcome these shortcomings, a novel MASS framework has been presented to forecast performance degradation and identify hazardous operating environments. The following are the main contributions of the suggested MASS method:

- Initially, the vibration data is collected during robot’s operation and this data is fed into SCB-LSTM model to classify the specific sources of vibration.
- The classified information is then sent to a remote monitoring application, allowing users to track the robot's condition in real-time.
- The primary advantage of the suggested method significantly enhances real-time monitoring and enabling efficient fault detection and maintenance planning through a remote app.
- Evaluations of the suggested MASS framework's performance have been conducted using evaluation metrics, including recall, accuracy, F1-score, and precision.

The remainder of the work has been organized as follows. Section 2 presents the literature review of PM in robots. Section 3 provides the suggested MASS technique in detail. Section 4 describes the experimental results and discussion in detail. Section 5 describes the conclusion section.

2. LITERATURE REVIEW

This section is to describe the health monitoring systems that can predict early signs of failure of industrial and machines robots that are discussed in this paper. Some of those techniques are briefly discussed in this section.

In 2023, Aivaliotis, P., et al., [20] proposed a generic PM framework (GPM) for complex machinery assets with multiple components and aspects in order to enable and execute the Digital Twin (DT) concept. The method's primary functions will be the planning of maintenance tasks and the evaluation of the machines' states. The work's findings demonstrate that developing, implementing, and running a DT with a 95% accuracy rate is achievable.

In 2023, Mourtzis, D., et al., [21] proposed a method that use DT as well as PM for the prediction of remaining useful life (RUL) to enhance the reliability of robotic cells. As a result of the current research's findings, suitable periodic maintenance can be implemented, ensuring high reliability and averting major robotic cell failures.

In 2023, Wang, X., et al., [22] provided a PM system that combines a decision support system for maintenance scheme assistance, a knowledge graph (KG) construction module for industrial robots (IRs), and a fault prediction module. The results demonstrate that the suggested system and approach function well when used on welding robots in a new energy car welding workplace.

In 2024, Chakroun, A., et al., [23] provided a PM method based on ML and AI called Discrete Bayes Filter (DBF) to evaluate and predict the slow degradation of robots' power transmitters. The objective is to enable operators to make knowledgeable judgments about maintenance interventions. The results show that the DBF method outperforms the Naïve Bayes Filter (NBF) method in terms of predictive performance.

In 2024, Kolvig-Raun, E.S., et al., [24] introduced a knowledge-based predictive model (KPM) that is intended to estimate a robotic joint's End of Life (EoL) so that its RUL can be predicted in relation to the specified load situation. With a lower limit of 90.3% for worst-case performance, the model exhibits a high degree of accuracy.

In 2024, Jeon, J.E., et al., [25] suggested a novel PM approach to forecast the wafer transfer robot's error and categorize the fault's significance degree. The benefit of the suggested approach is that it uses the Mean-Shift (MS) algorithm to classify the degree of errors and applies a more accurate Gaussian mixture model (GMM) to differentiate mistakes from normal data.

The approaches discussed above have certain shortcomings, including identifying a particular issue, its severity, or its RUL, and failing to take the external causes of degradation into consideration to predictive maintenance in robots. These flaws are effectively overcome by the suggested MASS technique, which is presented in the following section.

3. MAINTENANCE USING STACKED CNN BI-LSTM (MASS) SYSTEM

In this section, a novel MASS framework has been proposed for enhanced maintenance planning and real-time fault detection in cleaning robots. Initially, vibration data is collected during the robot's operation and categorized into normal, internal factors, or external factors. This data is processed through a SCB-LSTM to identify specific sources of vibration. The information is then sent wirelessly to a remote monitoring application, allowing users to track the robot's condition in real-time and diagnose issues efficiently. The block diagram for the suggested MASS method has been given in Figure 1.

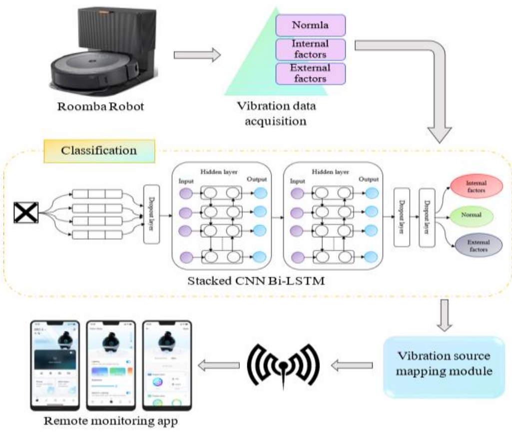


Figure 1. Overall proposed MASS technique

3.1. Autonomous cleaning robot "Roomba"

A Roomba robotic vacuum is an autonomous in-house cleaning device designed for automated floor vacuuming. The overall size of Roomba varies depending on the model, but typically it has a compact, round form factor, around 35 cm in diameter and weighing approximately 3-4 kg. The robot is equipped with an array of sensors and smart technologies to perform autonomous cleaning tasks. A central processing unit (CPU) manages the operation of the robot, including navigation, obstacle detection, and cleaning operations. Roomba uses a brush-and-suction mechanism to clean debris, with different brush systems suited for various surfaces like carpets and hardwood floors. Roomba can be controlled and monitored via a Wi-Fi connection through the iRobot Home app, providing remote control, scheduling, and status updates.

3.2. Vibration data acquisition phase

This module uses five vibration classes as key indications for operational safety concerns and deterioration in the performance of mobile cleaning robots. As seen in Figure 2, it falls into three categories: internal factors, normal, and external factors. In this case, internal causes are responsible for compilation and composition-induced vibrations, whereas exterior factors are responsible for surface and strike-induced vibrations.

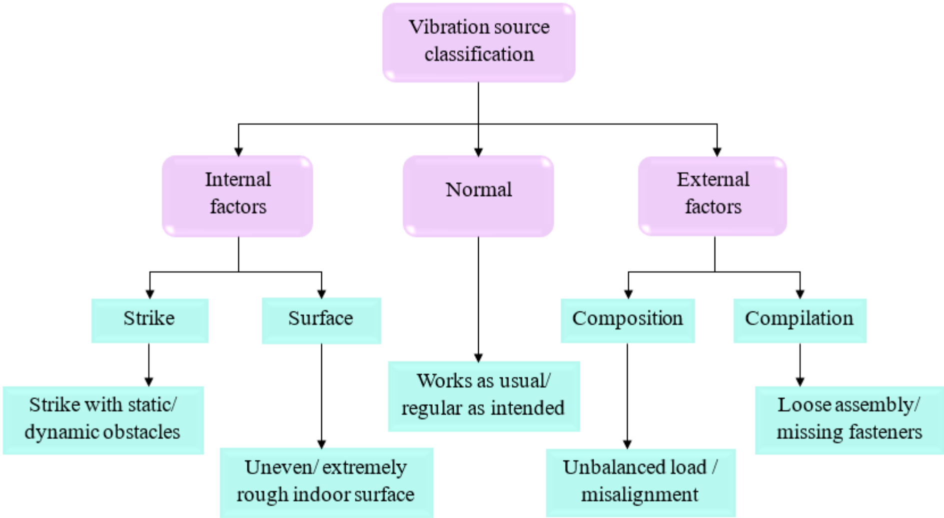


Figure 2. Classification of vibration sources

3.3. Classification using Stacked CNN Bi-LSTM (SCB-LSTM)

After the vibration data is acquired, this work uses SCB-LSTM to ensure both spatial and temporal information from the vibration signals are captured effectively for enhancing the classification accuracy. Experiments demonstrate that deep CNN and LSTM architectures with multiple hidden layers are capable of constructing increasingly complex representations of sequence data, and their performance is fairly good. This stacking-layers approach has the potential to improve neural network performance.

CNN may gather spatial feature dimensions and extract spatial feature vectors from the input data in its capacity as a feature detector. CNNs make sense as the foundational layer of the paradigm proposed in this paper. The previous sections covered the use of both forward and backward dependencies in Bi-LSTMs. Both the temporal dependence and the spatial correlation in various areas of the feature information can be recorded throughout the feature learning process when supplying the Bi-LSTMs with the input sequence. This means that the Bi-LSTMs are ideally suited to be the first or second layer in the suggested model, following CNN, in order to extract valuable information from time series data.

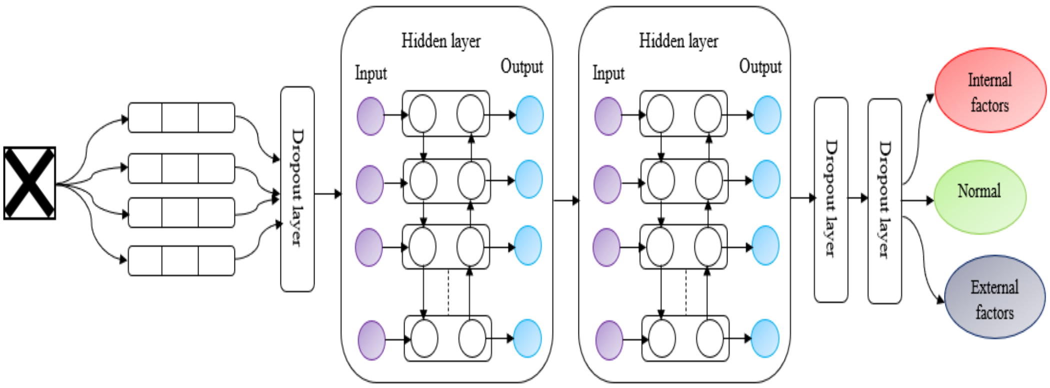


Figure 3. Architecture diagram of SCB-LSTM

The last layer of the design just needs to anticipate future values by iteratively calculating in the forward direction and producing projected values using learned features, or the outputs from lower layers. Therefore, it would be preferable to include an LSTM layer as the final layer in the suggested model in order to capture forward dependency.

To forecast the anomaly values, a deep architecture known as the SCB-LSTM was shown in Figure 3. The proposed model trains stacked bidirectional LSTMs (SB-LSTMs) for feature learning after using stacked CNNs to extract features from vibration sensor data. Following this process, the feature learning is improved by the stacked unidirectional LSTMs (SU-LSTM), and at the end, the regression layer makes a fault detection prediction.

3.4 Vibration source mapping phase

This module interprets the classification results and maps them to specific sources of vibration, helping to diagnose the cause of the vibrations. For instance, if an internal factor is detected, the system may identify a specific component in the Roomba that requires attention. A PM map is produced by continually fusing the vibration source classes produced by the prediction algorithm into the grid map. Using the PM map, the maintenance team or user can see what kinds of safety-related problems and performance deterioration are present in the deployment space.

3.5 Remote monitoring Phase

The Roomba robot's real-time prediction results can be visualized and controlled in teleoperation mode using a smart phone app, as illustrated in Figure 1. This gives users and technicians the ability to keep an eye on the Roomba's health in real time, giving them information about any possible problems or maintenance requirements. Using the MQTT messaging protocol, the app establishes a connection with the robot and gathers the anticipated data in either a request-based or continuous manner.

4. RESULT AND DISCUSSION

In this section, the suggestedMASS framework has been implemented on a MATLAB simulator. In order to assess the efficacy of the suggested MASS framework, it has been compared with other techniques, including TLS [16], HDL-AIDM [21], ACCeSS [23], and DTLS [25]. A number of important efficacy metrics such as F-measure, recall, accuracy and precision were evaluated in order to determine how well the MASS method performed.

4.1. System implementation

A component-oriented MASS approach has been developed, with an emphasis on the identification and categorization of malfunctioning behavior in the vital components of the robots. A DL algorithm has to be trained in order to finish developing the suggested technique. Both the data analysis and DL model training are done with MATLAB. In this study, SCB-LSTM are employed. Figure 4 denotes the proposed Roomba robot we used in this paper.

Figure 4. Hardware setup

4.2. Performance evaluation

The efficiency of the suggested MASS framework was compared with existing models such as GPM, DBF, and KPM. The technique's efficacy was evaluated utilizing the statistical measure metrics of precision, accuracy, F-measure, and recall (Equations (1)–(4)). According to the conventional confusion matrix, TN, TP, FN, and FP stand for true negatives, true positives, false negatives, and false positives, respectively.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (4)$$

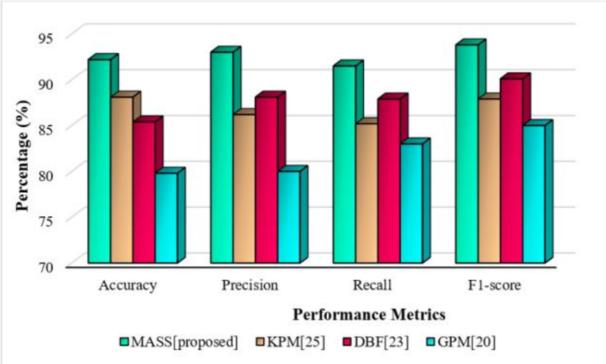
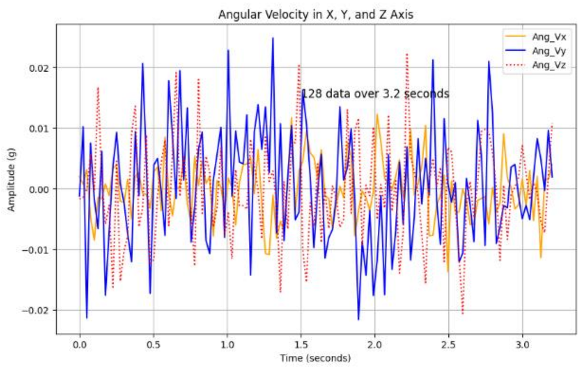
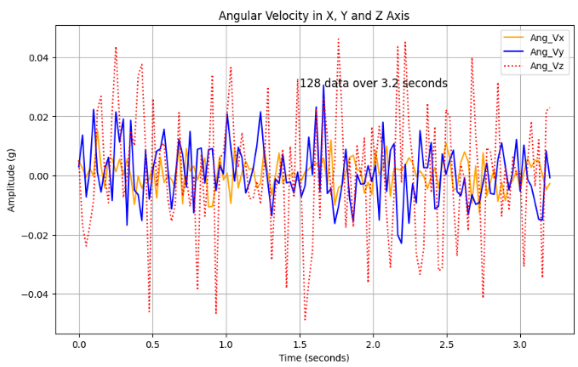


Figure 5. Performance analysis

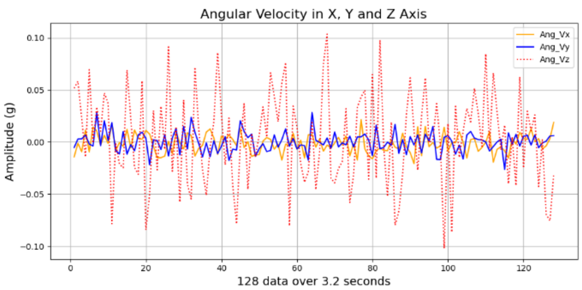
Figure 5 shows the recall, accuracy, f1-score, and precision comparison between the proposed MASS methodology and the current methods, including GPM, DBF, and KPM approaches. As can be seen from the comparison, the novel MASS method obtains an accuracy of 92.2%, which is greater than that of current methods like GPM [20], DBF [23], and KPM [25] models, which reach accuracy of 79.8%, 85.4%, and 88.1%, respectively.



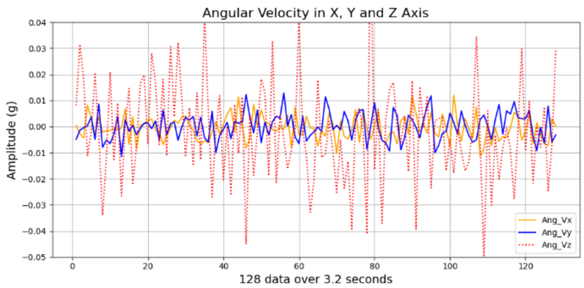
(a) Normal class



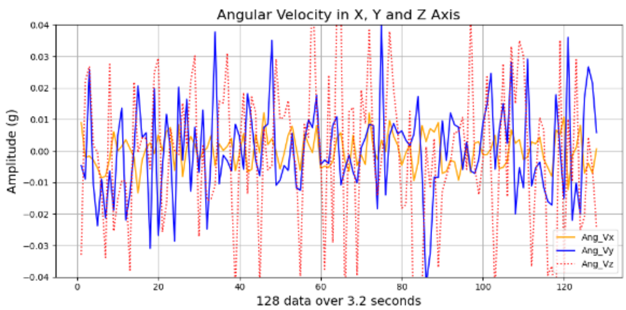
(b) Surface class



(c) Strike class



(d) Compilation class



(e) Composition class

Figure 6. Vibration signals with various classes

The time-amplitude graph for the raw vibration signal data obtained for each of the five classes across the three axes of each angular velocity signal type is displayed in Figure 6. The graphs show how the signals change as a function of various vibration source types visually. Plotted for a single sample of 128 data points, approximately 3.2 seconds of capture time.

5. CONCLUSION

In this research, a novel MASS approach has been suggested for enhanced maintenance planning and real-time fault detection in cleaning robots. We used an autonomous cleaning robot that we developed in-house to test and validate the suggested approach. Using the MATLAB simulator, a SCB-LSTM algorithm was created and trained on five vibration signal datasets produced by the Roomba robot under various health situations. The efficacy of the suggested MASS approach has been evaluated by utilizing parameters such as F1-score, recall, accuracy and precision respectively. The proposed MASS method achieves better accuracy of 79.8%, 85.4%, and 88.1% than GPM [20], DBF [23], and KPM [25] methods. Future work should enhance self-diagnosis and repair capabilities, optimizing robot design and maintenance strategies for greater operational efficiency and safety.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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